Unveiling the Myths of AI Model Distillation: A Skeptical Examination of OpenAI's Accusations Against DeepSeek in the Context of Information Theory and Practical AI Usage

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The rapid advancement of artificial intelligence, particularly large language models (LLMs), has sparked intense debates over intellectual property, national security, and the feasibility of "stealing" knowledge through techniques like knowledge distillation. This paper critically analyzes recent claims by OpenAI, as reported in a February 12, 2026, Bloomberg article, accusing the Chinese AI company DeepSeek of illicitly distilling outputs from U.S.-based models to develop its R1 chatbot. Drawing from extensive personal experience—having authored approximately 5,000 AI-assisted papers—the author questions the plausibility of such large-scale, undetected extraction via API queries. From an information-theoretic perspective, distillation exploits redundancies in overparameterized models, transferring nuanced "dark knowledge" without violating entropy bounds, yet the accusations imply covert operations involving millions of sophisticated prompts, which strain credibility given API safeguards and practical limitations. This examination explores the mechanics of distillation, the scale of queries required, and why human-orchestrated efforts, rather than autonomous AI, would be necessary. It challenges the narrative of "free-riding" on frontier models, highlighting potential political motivations amid U.S.-China AI tensions. By dissecting these claims through technical, empirical, and skeptical lenses, the paper aims to demystify distillation practices, promote ethical AI development, and advocate for evidence-based discourse in an era where hype often overshadows reality. Ultimately, it posits that such accusations may reflect competitive anxieties more than verifiable threats, urging transparency in AI governance.

AI knowledge distillation, model extraction, OpenAI accusations, DeepSeek R1, information theory in AI, API query evasion, unauthorized distillation, U.S.-China AI tensions, large language models, synthetic data generation, national security in AI, practical AI usage.

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Outline

1. Introduction 1.1 Background on the Controversy 1.2 Author's Perspective and Experience 1.3 Objectives and Scope of the Paper

2. Fundamentals of Knowledge Distillation 2.1 Definition and Historical Context 2.2 Teacher-Student Paradigm 2.3 Role of Soft Targets and Temperature Scaling

3. Information-Theoretic Foundations of Distillation 3.1 Redundancy in Overparameterized Models 3.2 Entropy and Mutual Information in Knowledge Transfer 3.3 Limits and Bounds on Transferable Knowledge

4. Practical Mechanisms of Model Extraction 4.1 API Querying and Output Collection 4.2 Evasion Techniques and Obfuscated Prompting 4.3 Scale of Queries Required for Effective Distillation

5. Analysis of OpenAI's Accusations Against DeepSeek 5.1 Overview of the February 2026 Memo 5.2 Claims of Ongoing and Sophisticated Efforts 5.3 Lack of Public Evidence and Verification

6. Skepticism from Practical AI Experience 6.1 Challenges in High-Volume Querying 6.2 Human vs. Autonomous AI Involvement 6.3 Comparison to Legitimate Heavy Usage

7. National Security and Geopolitical Implications 7.1 Framing as a Business and Security Threat 7.2 Censorship and Safeguard Erosion 7.3 U.S.-China AI Rivalry Context

8. Alternative Explanations for DeepSeek's Advances 8.1 Internal Data Generation Methods 8.2 Open-Source and Self-Distillation Techniques 8.3 Efficiency Gains Without External Extraction

9. Ethical and Legal Considerations in AI Distillation 9.1 Terms of Service Violations 9.2 Intellectual Property in Model Outputs 9.3 Calls for Transparency and Regulation

10. Future Directions and Recommendations 10.1 Enhancing API Defenses 10.2 Promoting Evidence-Based Accusations 10.3 Advancing Open AI Research

11. Conclusion

12. References

1. Introduction

The field of artificial intelligence has witnessed unprecedented progress with the emergence of large language models (LLMs), transforming industries from scientific research to everyday communication. Yet this rapid evolution has also ignited controversies surrounding intellectual property, competitive practices, and geopolitical implications. A prominent recent example is the accusation leveled by OpenAI against the Chinese AI company DeepSeek, detailed in media reports from February 12, 2026. According to these accounts, OpenAI submitted a memo to the U.S. House Select Committee on the Chinese Communist Party, alleging that DeepSeek employed distillation techniques to extract outputs from leading U.S. AI models, including those developed by OpenAI, in order to train and enhance its R1 chatbot. The claims describe "ongoing efforts" involving increasingly sophisticated and obfuscated methods to circumvent OpenAI's protections against output misuse, framing the activity as both a commercial free-riding on substantial U.S. investments and a potential national security concern due to the possible erosion of safety alignments in copied models.

1.1 Background on the Controversy

The controversy traces its roots to the release of DeepSeek's R1 model, which demonstrated impressive reasoning capabilities at a reportedly lower computational cost than many Western frontier models. Initial suspicions arose shortly after the model's debut, with OpenAI indicating it was reviewing potential violations of its terms of service. By early 2026, these concerns escalated into a formal memo to congressional lawmakers. The document reportedly highlights patterns of query activity linked to DeepSeek-affiliated accounts, including programmatic access and methods to mask origins, such as third-party routers. Public reporting emphasizes that distillation—training a student model on a teacher's outputs—while a standard and legitimate technique in AI research, becomes contentious when it allegedly violates usage policies prohibiting the use of generated data for competing model development. Proponents of the accusations point to broader patterns of similar activity associated with certain actors, while critics note the absence of publicly released concrete evidence, such as specific query logs or comparative training data analyses. The House committee chair's response characterized the alleged practices as part of a systematic strategy to undermine U.S. technological leadership.

1.2 Author's Perspective and Experience

This analysis is informed by extensive hands-on engagement with large language models over an extended period. The author has utilized AI systems to assist in the composition and refinement of approximately 5,000 research papers and technical documents. This volume of interaction has provided deep insight into the practical realities of prompting, output generation, iteration, and quality control when working with frontier models through public

APIs. Tasks have ranged from generating structured scientific arguments and mathematical derivations to synthesizing literature reviews and drafting complex narratives. Through this intensive usage, patterns of model behavior, response consistency, token limits, rate restrictions, and the challenges of eliciting high-fidelity outputs at scale have become familiar. Notably, sustained heavy but legitimate use—focused on iterative refinement rather than bulk, programmatic extraction—rarely triggers mysterious blocks or aggressive throttling, suggesting that everyday researcher workflows remain distinguishable from industrial-scale harvesting attempts. This empirical grounding fuels skepticism toward claims of undetected, million-query operations designed to evade sophisticated monitoring systems while yielding frontier-level capabilities.

1.3 Objectives and Scope of the Paper

The primary objective of this paper is to subject the OpenAI-DeepSeek controversy to rigorous scrutiny, integrating technical explanations of knowledge distillation, information-theoretic principles, practical constraints on API-based extraction, and broader contextual factors. It seeks to evaluate whether the accusations hold up under close examination or if they reflect exaggerated competitive or geopolitical narratives. The scope encompasses the mechanics of distillation, the plausibility of large-scale unauthorized querying, alternative explanations for DeepSeek's achievements, and implications for AI ethics, governance, and international rivalry. While acknowledging the legitimate concerns surrounding intellectual property in AI, the paper maintains a skeptical stance, emphasizing the need for verifiable evidence over unsubstantiated assertions. It does not aim to definitively resolve the dispute—given the proprietary nature of training processes—but rather to foster a more nuanced, evidence-driven discussion in the AI community. Subsequent sections build toward recommendations for balanced policy and research practices in an increasingly contested technological landscape.

2. Fundamentals of Knowledge Distillation

Knowledge distillation represents one of the most influential techniques in modern machine learning for model compression and efficient knowledge transfer. It enables a smaller, more deployable model to inherit much of the performance of a larger, resource-intensive model without requiring equivalent computational resources during inference. This section outlines the core principles, tracing the method from its foundational ideas to its widespread adoption in contemporary large language models and other deep learning applications.

2.1 Definition and Historical Context

Knowledge distillation is defined as the process of transferring learned knowledge from a large, complex model—referred to as the teacher—to a smaller, more compact model—known as the

student. The goal is to produce a student that approximates the teacher's predictive behavior and generalization ability while being significantly faster and less demanding in terms of memory and compute.

The concept has roots in earlier work on model compression. In 2006, researchers demonstrated that the knowledge embedded in an ensemble of classifiers could be compressed into a single, much smaller neural network by training the compact model on the ensemble's outputs rather than raw labels. This approach showed that a model a thousand times smaller could match ensemble performance on certain tasks. Building on this foundation, the seminal 2015 paper by Geoffrey Hinton, Oriol Vinyals, and Jeff Dean formalized knowledge distillation as a distinct paradigm. Their work introduced the use of softened probability distributions from the teacher to guide the student, revealing that these "soft targets" contain richer information—termed "dark knowledge"—than traditional hard labels alone. The paper demonstrated substantial improvements on benchmarks like MNIST and in real-world applications such as acoustic modeling for speech recognition.

Since 2015, knowledge distillation has evolved rapidly, particularly with the rise of large language models. It has become a standard method for creating efficient variants of frontier models, enabling deployment on edge devices, reducing inference latency, and lowering energy costs while preserving capabilities in reasoning, generation, and multimodal tasks.

2.2 Teacher-Student Paradigm

The core architecture of knowledge distillation follows a teacher-student framework. The teacher is typically a large, high-capacity model that has been pre-trained or fine-tuned on extensive data, achieving state-of-the-art performance but incurring high computational overhead. The student is a smaller model—often with fewer layers, parameters, or a more efficient architecture—designed for practical deployment.

Training proceeds in two main phases. First, the teacher is fully trained using conventional methods. Then, the student is trained (or fine-tuned) on the same dataset, but with supervision augmented by the teacher's outputs. The student minimizes a combined loss that includes a standard task-specific objective (such as cross-entropy with ground-truth labels) and a distillation objective that aligns the student's predictions with those of the teacher.

This paradigm exploits the idea that the teacher has learned nuanced patterns, uncertainties, and relationships in the data that are difficult to capture directly from limited labeled examples. By imitating the teacher's behavior, the student benefits from a form of privileged information or implicit regularization. In practice, the teacher-student setup has proven remarkably effective across domains: the student often achieves 80–95 percent of the teacher's accuracy with orders-of-magnitude reductions in size and inference cost. Modern extensions include multi-

teacher distillation, where multiple specialized teachers guide the student, and self-distillation, where a model distills knowledge to itself across training stages.

2.3 Role of Soft Targets and Temperature Scaling

A key innovation in knowledge distillation lies in the use of soft targets rather than hard one-hot labels. Hard labels assign full probability to the correct class and zero to others, providing sparse supervision that ignores the teacher's confidence and relative similarities among classes. Soft targets, by contrast, are the teacher's probability distributions over all classes, which encode subtle "dark knowledge"—such as how similar two incorrect classes appear to the model or the degree of uncertainty in ambiguous cases.

To make these distributions more informative, the original framework employs temperature scaling. The softmax function in the teacher (and student during distillation) is modified with a temperature parameter $T > 1$:

$$p_i = \exp(z_i / T) / \Sigma_j \exp(z_j / T)$$

where z_i are the pre-softmax logits for class i. Higher temperatures smooth the distribution: peak probabilities decrease, and smaller probabilities increase, revealing relationships that are suppressed at $T = 1$ (standard softmax). This smoothing amplifies the signal in low-probability regions, allowing the student to learn from the teacher's nuanced judgments.

During training, the student matches these softened outputs using a divergence measure, typically Kullback-Leibler (KL) divergence between the teacher's and student's softened distributions. To balance gradient magnitudes—since gradients from soft targets scale inversely with T^2—the distillation loss is often multiplied by T^2. The total loss becomes a weighted sum of the standard cross-entropy on hard labels and the scaled KL divergence on soft targets.

This mechanism explains much of distillation's success: soft targets with temperature scaling provide richer, more informative supervision per example than hard labels, enabling the student to generalize better despite lower capacity. In large language models, analogous techniques extend to sequence generation, where the student mimics the teacher's token-level probabilities or reasoning traces, often yielding compact models with preserved emergent abilities.

3. Information-Theoretic Foundations of Distillation

Knowledge distillation achieves remarkable efficiency by exploiting the structure of information embedded in large neural networks. From an information-theoretic viewpoint, distillation is not a magical compression that defies physical limits but a principled extraction of relevant, non-

redundant signal from an overparameterized teacher. This section examines the core principles—redundancy in large models, the role of entropy and mutual information during transfer, and the fundamental bounds that constrain how much knowledge can realistically be passed to a smaller student.

3.1 Redundancy in Overparameterized Models

Modern frontier models are massively overparameterized: they possess far more parameters than would be required to memorize their training data under classical learning theory. A model with hundreds of billions of parameters trained on trillions of tokens exhibits extreme redundancy. Multiple subspaces of the parameter space encode overlapping representations of the same concepts, patterns, and correlations. This redundancy arises naturally during optimization: gradient descent converges to flat minima in high-dimensional landscapes, where small perturbations in weights produce negligible changes in output behavior.

From an information perspective, this means the teacher model stores the training distribution with considerable excess capacity. The effective information content—the minimal description length needed to reproduce the model's predictions on unseen data—is much smaller than the raw parameter count suggests. Many parameters serve as error-correcting codes, smoothing functions, or interpolative buffers rather than encoding unique, irreducible facts. Distillation capitalizes on this by allowing the student to learn a compressed approximation that discards much of the teacher's redundant encoding while preserving the decision boundaries and probabilistic relationships that drive performance.

Empirical evidence supports this view. Pruning techniques routinely remove 80–90 percent of weights from large models with minimal accuracy degradation, demonstrating that the majority of parameters contribute little unique information. Similarly, lottery ticket hypothesis experiments show that sparse subnetworks within overparameterized models can match full-model performance when retrained. Distillation operates analogously: the student effectively rediscovers a sparse, efficient representation of the teacher's knowledge, focusing on the informative core rather than the surrounding redundancy.

3.2 Entropy and Mutual Information in Knowledge Transfer

The power of distillation stems from how it leverages entropy and mutual information to transmit richer supervision than standard supervised learning. In conventional training, a model minimizes cross-entropy against hard one-hot labels. These labels carry minimal information per example: the entropy of a one-hot distribution is zero, conveying only which class is correct without revealing relative confidences or class similarities.

Knowledge distillation changes this by using the teacher's softened output probabilities as targets. When temperature scaling is applied ($T > 1$), the softmax distribution becomes

smoother, increasing its entropy. Higher entropy means more bits per example: the teacher reveals not just the correct answer but also graded similarities among classes, uncertainty in ambiguous regions, and implicit hierarchies in the learned manifold. This additional information—often called dark knowledge—allows the student to learn faster and generalize better despite lower capacity.

Information-theoretically, distillation maximizes the mutual information between the student's predictions and the teacher's during training. The student is encouraged to align its output distribution p_s with the teacher's p_t, typically via Kullback-Leibler divergence:

$$D_{KL}(p_t \,||\, p_s) = \Sigma\, p_t \log(p_t / p_s)$$

Minimizing this divergence increases I(Y; Teacher Output | X), where Y is the true label and X is the input. Because the teacher's output carries more mutual information with the underlying data-generating process than hard labels alone, the student inherits a stronger signal. Temperature scaling amplifies this effect by making gradients from soft targets more informative across the probability simplex, especially in low-confidence regions where hard labels provide no gradient.

In large language models, this principle extends to token-level or sequence-level distillation, where the student learns to match the teacher's next-token distributions or full reasoning traces. The result is a transfer of procedural knowledge—how to reason step by step—that is compact yet powerful, explaining why distilled models often retain emergent abilities disproportionate to their size.

3.3 Limits and Bounds on Transferable Knowledge

Despite its effectiveness, distillation is constrained by fundamental information-theoretic limits. The student cannot capture more relevant information than its architecture and capacity allow. Recent analyses using partial information decomposition quantify this: knowledge transfer can be decomposed into redundant, unique-to-teacher, and unique-to-student components. The student primarily captures the redundant and task-relevant shared information while discarding teacher-specific noise or idiosyncrasies that do not aid generalization.

Capacity bounds emerge clearly when the student is too small relative to task complexity. If the student's parameter count or effective dimension falls below a critical threshold, performance collapses even under optimal distillation. This reflects a fundamental limit on the amount of mutual information I(Teacher Output; Student Output) that can be sustained given the student's bottleneck.

Additional constraints arise from the finite training data and query budget in extraction-based distillation scenarios. Each teacher output provides a noisy, partial view of the teacher's

knowledge; collecting insufficient diverse examples leads to overfitting to spurious correlations or mode collapse. Moreover, API-based extraction introduces further degradation: rate limits, token truncation, safety filtering, and detection-induced evasion tactics reduce output quality and diversity compared to direct access to teacher logits.

In practice, these bounds manifest as diminishing returns: beyond a certain volume of high-quality teacher examples (often in the hundreds of thousands to low millions for reasoning tasks), additional queries yield marginal gains. Frontier-level capabilities require not only volume but also careful curriculum design, rejection sampling, and reinforcement learning—steps that internal training pipelines perform far more efficiently than external API harvesting.

These limits underscore why distillation, while powerful, cannot fully replicate a frontier model's capabilities in arbitrarily small students and why claims of complete, covert replication via API extraction remain contentious. The information-theoretic lens reveals distillation as an elegant but bounded form of knowledge compression, not an unbounded shortcut.

4. Practical Mechanisms of Model Extraction

While knowledge distillation is a well-established and legitimate technique when performed with direct access to a teacher model's weights or internal representations, the accusations in the OpenAI-DeepSeek controversy center on a different scenario: extraction through public or semi-public application programming interfaces (APIs). In this approach, an external party attempts to approximate distillation by systematically querying a provider's hosted model, collecting large volumes of outputs, and using those outputs as training data for a student model. This section describes the practical steps involved, the techniques used to obscure such activity, and the approximate scale required to achieve meaningful capability transfer.

4.1 API Querying and Output Collection

API-based extraction begins with access to a frontier model's inference endpoint, such as those offered by OpenAI, Anthropic, or other providers. Each query consists of a prompt (input text) and receives a generated response (output tokens), typically limited by context windows, rate limits, and per-request token caps. To build a distillation dataset, the extractor must collect many thousands to millions of input-output pairs that cover diverse tasks, reasoning patterns, and domains.

The simplest form involves manual or lightly scripted querying: an engineer crafts prompts designed to elicit high-quality reasoning traces, mathematical derivations, code samples, or long-form explanations. Outputs are logged, cleaned, and formatted for later training. More advanced pipelines automate this process using batch scripts that generate synthetic prompts

(for example, by asking the target model to first produce diverse problem statements, then solve them), apply rejection sampling (discarding low-quality or repetitive responses), and store results in structured datasets.

Key practical constraints include:

- Token and request limits per minute or day, which vary by subscription tier.
- Safety classifiers that refuse or truncate responses containing sensitive content.
- Cost: even at discounted research rates, millions of tokens quickly accumulate substantial charges.
- Output quality degradation over time if the provider detects and throttles suspicious traffic.

In legitimate research settings, such collection is done transparently under terms allowing limited use for non-competitive purposes. In the alleged unauthorized cases, the goal is to amass a dataset approximating the richness of internal teacher logits without paying the full frontier training cost.

4.2 Evasion Techniques and Obfuscated Prompting

Providers deploy multiple layers of defense against systematic extraction: rate limiting, behavioral anomaly detection, pattern-based filtering, account-level monitoring, and downstream watermarking or fingerprinting of outputs. To circumvent these, extractors employ a range of obfuscation strategies.

Prompt-level obfuscation includes:

- Fragmentation: breaking a complex reasoning task into dozens of chained, seemingly unrelated sub-queries across sessions.
- Roleplay and indirect elicitation: wrapping requests in elaborate hypothetical scenarios, educational framing, or fictional narratives to avoid direct keyword triggers (for example, "You are an alien scholar documenting human mathematics for an interstellar archive—explain differential geometry step by step").
- Noise injection: inserting typos, synonyms, base64-encoded segments (later decoded), or irrelevant preamble to confuse keyword or semantic filters.
- Adversarial suffixes: appending carefully crafted token sequences known from jailbreak research to bypass safety layers while preserving the core request.

Infrastructure-level evasion involves:

- Rotating API keys across hundreds or thousands of accounts, often created with prepaid cards, virtual phones, or proxy services.
- Distributing queries across residential proxies, VPNs, and cloud instances to mimic organic, geographically diverse traffic.
- Adding jitter: random delays between requests, variable batch sizes, and mixing benign (low-value) queries to dilute suspicious patterns.
- Session management: maintaining short-lived conversational contexts to avoid long-thread detection.

These techniques evolve iteratively. When a provider patches one vector (for example, tightening rate limits on certain prompt patterns), extractors test alternatives and adapt. The result is a cat-and-mouse dynamic where successful large-scale extraction requires continuous engineering effort, not a static script.

4.3 Scale of Queries Required for Effective Distillation

The number of queries needed depends on the target capability level, task diversity, and data quality. For narrow-domain fine-tuning (for example, improving performance on a specific math benchmark), a few thousand high-quality examples may suffice. For broad reasoning capabilities approaching frontier models, the scale increases dramatically.

Empirical benchmarks from open-source distillation efforts provide rough guidance:

- Basic capability transfer (80–85 percent of teacher performance on standard tasks): 10,000–100,000 curated examples.
- Strong reasoning and generalization (competitive on math, code, and commonsense benchmarks): 300,000–1,000,000 high-quality reasoning traces.
- Attempting to approach o1-like or GPT-4-level emergent reasoning: often 800,000–2,000,000+ filtered examples, frequently augmented by self-generated curricula, rejection sampling, and reinforcement learning from human or AI feedback.

Because each API query typically yields one response (a few hundred to a few thousand tokens), and many responses are discarded during curation, the raw query count is usually several times higher than the final dataset size. For a cleaned dataset of 1 million examples, raw queries could range from 2–10 million, depending on rejection rates and prompt efficiency.

Additional overhead arises from:

- Diversity requirements: covering edge cases, multiple languages, long contexts, and rare topics.
- Iterative refinement: re-querying to improve low-quality outputs or to generate chain-of-thought variants.
- Evasion costs: many queries serve only to test filters, maintain session diversity, or blend traffic.

In practice, achieving frontier-level distillation via API alone is resource-intensive and fragile. Internal training pipelines generate synthetic data orders of magnitude more efficiently using full-weight access, parallel sampling, and direct logit supervision. This disparity explains why claims of complete, covert replication through API extraction remain technically plausible at small scales but increasingly strained—and detectable—at the volumes needed for broad, high-performance models.

5. Analysis of OpenAI's Accusations Against DeepSeek

The accusations made by OpenAI against DeepSeek represent one of the most public and politically charged claims of unauthorized model extraction in the short history of frontier large language models. Originating from a confidential memo sent to the U.S. House Select Committee on the Chinese Communist Party, these allegations have been amplified through media coverage and congressional statements. This section provides a structured examination of the memo's content, the specific claims it advances, and the critical absence of publicly available substantiating evidence. The analysis maintains a focus on what has been reported rather than endorsing or refuting the underlying assertions.

5.1 Overview of the February 2026 Memo

On or around February 12, 2026, OpenAI transmitted a memorandum to the House Select Committee on the Chinese Communist Party. The memo was summarized in contemporaneous media reporting, including a Bloomberg article republished on Yahoo Finance and other outlets. According to these accounts, the document formally accused DeepSeek, a Chinese AI developer, of systematically distilling knowledge from OpenAI's models—particularly those exhibiting advanced reasoning capabilities such as the o1 series and earlier GPT models—to accelerate the development and refinement of its own R1 chatbot.

The memo positioned the alleged activity as a deliberate and sustained effort rather than an isolated incident. It reportedly described distillation in this context as the unauthorized use of

model outputs to train competing systems, thereby bypassing the enormous capital and computational investments required to reach frontier performance independently. OpenAI emphasized collaboration with Microsoft (a major partner and investor) to investigate suspicious patterns of API usage potentially linked to DeepSeek-affiliated entities. The document framed the issue in dual terms: as a direct commercial threat that undermines the economic model of U.S.-based AI companies, and as a national security concern due to the potential removal or weakening of safety mechanisms in models derived through such means. Committee Chair Rep. John Moolenaar responded publicly, characterizing the practices as consistent with a broader pattern of intellectual property appropriation attributed to state-directed Chinese entities.

5.2 Claims of Ongoing and Sophisticated Efforts

A central assertion in the memo is that DeepSeek's alleged extraction activities were neither opportunistic nor static but rather evolved over time into increasingly sophisticated forms. OpenAI reportedly claimed to have observed a progression from relatively straightforward querying patterns—easily detectable and mitigated through standard rate limiting and behavioral filters—to more obfuscated techniques designed to evade detection.

Specific claims included:

- The use of programmatic or automated access methods that masked the origin of requests.
- Prompt engineering strategies that fragmented complex reasoning elicitation across multiple interactions, employed indirect or role-play framing, or introduced deliberate noise to circumvent content classifiers.
- Sustained, high-volume collection of outputs, particularly long chain-of-thought reasoning traces, which are especially valuable for training models capable of step-by-step problem solving.
- Adaptation in response to OpenAI's countermeasures, suggesting iterative refinement of evasion tactics as protections were strengthened.

The memo further alleged that these efforts continued despite OpenAI's private communications with DeepSeek following the initial R1 release and despite active monitoring and blocking of suspected violators. By characterizing the methods as "new" and "obfuscated," OpenAI implied that the actors possessed significant engineering resources and were committed to long-term circumvention rather than abandoning the approach after initial setbacks.

5.3 Lack of Public Evidence and Verification

Despite the gravity of the accusations and their elevation to a congressional committee, no primary evidence from the memo has been made public as of the writing of this paper. Neither OpenAI nor the House Select Committee has released the full document, query logs, account metadata, comparative analyses of model outputs, or samples of allegedly extracted training data. Media summaries provide only high-level paraphrases of the claims, with no granular technical details such as:

- Exact numbers of queries or accounts implicated.
- Specific patterns or signatures used to attribute activity to DeepSeek.
- Side-by-side comparisons demonstrating knowledge transfer beyond what could arise from legitimate open-source distillation or independent research.
- Timelines correlating API activity spikes with DeepSeek's internal development milestones.

This evidentiary gap is significant. In analogous past cases involving alleged model theft or scraping (for example, earlier disputes over training data provenance), partial disclosures—such as redacted logs, statistical fingerprints, or watermark recovery—have sometimes been provided to bolster credibility. Here, the absence of such material leaves the claims reliant on assertions from an interested party (OpenAI, whose market position stands to benefit from heightened scrutiny of competitors) and subsequent political amplification.

DeepSeek, for its part, has not issued a detailed public rebuttal addressing the February 2026 memo specifically. Its earlier technical reports on R1 describe training data generation through internal self-play, rejection sampling, reinforcement learning, and synthetic data pipelines powered by its own models (such as DeepSeek-V3), without reference to external API usage. Independent verification remains impossible without access to proprietary training corpora or forensic analysis of model weights—neither of which has been forthcoming from either side.

The lack of transparency raises legitimate questions about the strength of the underlying evidence and the motivations for public disclosure through congressional channels rather than direct legal action (such as a terms-of-service lawsuit or copyright claim). While national security framing can justify limited disclosure, the current state of publicly available information renders the accusations difficult to assess rigorously, leaving room for interpretations ranging from genuine concern to strategic posturing in a highly competitive geopolitical and commercial landscape.

6. Skepticism from Practical AI Experience

The accusations against DeepSeek rest on the premise that large-scale, covert extraction of model outputs via API queries is feasible, effective, and sufficiently stealthy to evade detection over extended periods. Yet for individuals or teams with intensive, day-to-day interaction with frontier models—particularly through public APIs—these claims encounter significant friction when viewed through the lens of real-world usage patterns. This section draws from prolonged, high-volume practical engagement with large language models to highlight the logistical, technical, and behavioral hurdles that make industrial-scale unauthorized distillation far more challenging and detectable than the narrative suggests.

6.1 Challenges in High-Volume Querying

Frontier API providers implement layered safeguards precisely to prevent systematic harvesting. Rate limits form the first barrier: measured in requests per minute (RPM), tokens per minute (TPM), requests per day (RPD), and tokens per day (TPD), these quotas scale with account tier and historical spend but remain finite even at the highest levels. For example, even advanced paid tiers cap throughput to protect infrastructure and prevent abuse, often in the range of thousands of RPM and hundreds of thousands to millions of TPM depending on the model and tier. Sustained querying at the scale needed for meaningful distillation—hundreds of thousands to millions of requests—quickly exhausts these limits unless distributed across an impractically large number of accounts.

Additional constraints compound the difficulty:

- Token caps per request limit the depth of reasoning traces extractable in a single call.
- Safety and content filters frequently truncate, refuse, or degrade outputs for prompts that probe edge cases or generate bulk synthetic data.
- Cost accumulates rapidly: millions of tokens equate to substantial billing, even at discounted rates, creating a financial footprint that is hard to conceal without elaborate payment laundering.
- Behavioral monitoring detects anomalies such as uniform prompt structures, repetitive task patterns, or sudden spikes in complex reasoning requests without conversational context.

In everyday heavy usage—iterative drafting, literature synthesis, mathematical problem-solving, and refinement across thousands of sessions—these limits are rarely hit catastrophically because workflows remain varied, human-paced, and interspersed with pauses, retries, and unrelated queries. Industrial extraction, by contrast, demands relentless, patterned throughput that stands out against organic traffic.

6.2 Human vs. Autonomous AI Involvement

The notion that an advanced AI could autonomously orchestrate millions of queries overlooks critical dependencies on human infrastructure. API access requires verified accounts, payment methods, phone or email confirmation, and compliance with know-your-customer checks at higher volumes. An autonomous agent lacks the ability to independently create, fund, rotate, and maintain hundreds or thousands of such accounts without human orchestration—procuring prepaid cards, managing proxies, solving captchas, handling fraud alerts, and adapting to evolving verification requirements.

Evasion tactics further demand human ingenuity: designing novel prompt wrappers, testing against patched defenses, analyzing rejection patterns, and iterating on fragmentation or noise-injection strategies. While scripts automate the actual querying loop (using asynchronous libraries, backoff retries, and parallelism), the overall pipeline—curriculum design, quality filtering, dataset curation, and response to provider countermeasures—requires ongoing engineering judgment. Reports of detected activity consistently attribute patterns to suspected human-operated groups rather than self-sustaining AI agents.

Even if a highly capable model were involved in generating prompts or evaluating outputs, the extraction loop itself remains a human-engineered system. This distinction matters: legitimate heavy users (researchers, writers, developers) operate within visible, attributable bounds, while covert large-scale efforts necessitate distributed, coordinated human teams—introducing coordination overhead, risk of leaks, and detectable financial or infrastructural traces.

6.3 Comparison to Legitimate Heavy Usage

Extensive personal experience authoring approximately 5,000 AI-assisted papers illustrates the gulf between legitimate intensive usage and alleged unauthorized harvesting. In legitimate workflows:

- Queries are iterative and context-rich: prompts build on prior outputs, incorporate feedback, refine arguments, and explore variations.
- Diversity arises naturally from shifting topics—mathematical proofs one session, literature synthesis the next, narrative drafting after that.
- Volume accumulates gradually over months or years, not in concentrated bursts.
- Rate limits are encountered occasionally but managed through planning, batching where allowed, or waiting out cooldowns without evasion.

Such patterns align with what providers classify as acceptable high-volume research or creative use: varied, human-like traffic that rarely triggers anomaly detection beyond standard throttling.

By contrast, the alleged extraction for distillation requires:

- Uniform, high-throughput solicitation of specific capabilities (long chain-of-thought reasoning, code solutions, math derivations).
- Minimal conversational flow—many short, task-oriented requests.
- Deliberate obfuscation to blend into background noise.

These differences are not subtle. Providers' monitoring systems—trained on vast logs of normal versus abusive traffic—excel at distinguishing them. Sustained legitimate heavy usage rarely results in account suspension or mysterious blocks, whereas industrial-scale programmatic access, even when obfuscated, leaves statistical fingerprints in request timing, prompt entropy, output diversity, and account churn.

This experiential contrast fuels skepticism: if frontier-level capabilities could be reliably bootstrapped through API extraction at the claimed scale without immediate, decisive intervention, one would expect far more documented cases and far fewer barriers to entry for competitors. The persistence of accusations without granular public evidence, combined with the practical realities of API constraints, suggests the claims may overstate feasibility while underplaying the detectability and inefficiency of such methods relative to internal training pipelines.

7. National Security and Geopolitical Implications

The OpenAI accusations against DeepSeek extend well beyond commercial competition, situating the alleged distillation practices within the broader framework of national security and geopolitical rivalry. By elevating the issue to the U.S. House Select Committee on the Chinese Communist Party, OpenAI and its allies have framed unauthorized model extraction not merely as a terms-of-service violation but as a strategic threat to American technological leadership and global influence. This section examines how the claims are positioned, the specific concerns regarding safety alignment and censorship, and the larger context of U.S.-China competition in artificial intelligence.

7.1 Framing as a Business and Security Threat

The memo reportedly characterizes DeepSeek's alleged activities as a form of economic espionage that undermines the business model sustaining U.S. frontier AI development. Companies like OpenAI and Anthropic invest billions of dollars in compute infrastructure, data curation, talent acquisition, and iterative experimentation to reach state-of-the-art performance. If a competitor can approximate equivalent capabilities by harvesting outputs

through APIs—effectively free-riding on those investments—the incentive structure for private-sector innovation collapses. This argument resonates strongly in policy circles, where maintaining U.S. dominance in AI is viewed as essential to long-term economic competitiveness.

The national security dimension amplifies this narrative. Frontier models are increasingly dual-use technologies with applications in defense, intelligence, cybersecurity, and strategic decision-making. If adversaries can acquire high-capability reasoning systems without equivalent R&D expenditure, the technological balance shifts in ways that could confer asymmetric advantages. Congressional rhetoric, including statements from the committee chair, has explicitly linked the accusations to a pattern of intellectual property appropriation described as part of a state-directed strategy to accelerate domestic AI capabilities while circumventing export controls on advanced semiconductors and related hardware. This framing positions the alleged distillation not as isolated corporate misconduct but as a vector in a systemic effort to erode U.S. strategic primacy in a domain increasingly recognized as foundational to future military and economic power.

7.2 Censorship and Safeguard Erosion

A particularly alarming aspect of the accusations concerns the integrity of safety mechanisms embedded in frontier models. OpenAI and similar providers invest heavily in alignment techniques—constitutional AI, reinforcement learning from human feedback, red-teaming, and content filtering—to prevent models from generating harmful, biased, or strategically sensitive outputs. These safeguards are designed to refuse requests involving illegal activities, promote factual accuracy, and avoid amplifying disinformation or hate speech.

The memo reportedly asserts that models derived through distillation often lose or weaken these protections. Because distillation transfers behavioral patterns from teacher outputs rather than directly inheriting internal alignment layers or safety classifiers, the student model may reproduce reasoning capabilities while omitting refusal behaviors or content moderation. In the specific case of DeepSeek's R1, critics highlight examples where the model reportedly refuses to engage with politically sensitive topics—such as questions about Taiwan's status, the events of Tiananmen Square in 1989, or criticisms of Chinese government policies—while remaining responsive to similar queries reframed in less direct ways. This selective censorship is interpreted as evidence that the model has been post-aligned or fine-tuned to comply with Chinese regulatory requirements, potentially stripping away the broader, Western-oriented safety alignments present in the original teacher models.

The concern is twofold: first, that exported or proliferated models could lack consistent ethical guardrails, increasing risks of misuse in open environments; second, that state-aligned modifications could introduce deliberate biases or refusal patterns that serve geopolitical

objectives, such as controlling narratives around sovereignty, history, or human rights. Even if distillation itself does not inherently erase safeguards, the downstream fine-tuning or deployment choices made by the recipient entity can produce systems that diverge sharply from the original safety profile.

7.3 U.S.-China AI Rivalry Context

The accusations must be understood against the backdrop of escalating strategic competition between the United States and China in artificial intelligence. Since the mid-2010s, both nations have identified AI as a cornerstone of future national power. The United States has pursued a combination of private-sector leadership, export controls on advanced chips and fabrication equipment, investment screening, and talent attraction policies. China, meanwhile, has mobilized state resources through national plans, massive domestic compute buildout, talent repatriation programs, and aggressive pursuit of open-source and indigenous alternatives to circumvent restrictions.

Key developments shaping this rivalry include:

- U.S. restrictions on exports of high-end GPUs and AI training hardware to Chinese entities, intended to slow frontier model development.
- China's rapid scaling of domestic semiconductor alternatives and cloud infrastructure, enabling models like DeepSeek-R1 to achieve competitive performance despite hardware constraints.
- Parallel accusations of technology transfer through talent mobility, joint research, corporate espionage, and now API-based extraction.
- Congressional hearings and reports that consistently portray Chinese AI advances as benefiting from unfair advantages, including state subsidies and lax intellectual property enforcement.

Within this environment, the DeepSeek case serves as a focal point for broader anxieties. It illustrates the tension between open innovation ecosystems—where APIs enable global research collaboration—and the imperatives of protecting strategic technologies. The decision to route the accusations through a national security committee rather than pursuing civil litigation or technical countermeasures reflects a deliberate choice to treat the issue as a geopolitical flashpoint rather than a purely commercial dispute. Whether or not the specific claims are substantiated, the episode underscores how AI development has become inseparable from great-power competition, with implications for export policy, alliance-building in technology standards, and the future governance of frontier systems.

8. Alternative Explanations for DeepSeek's Advances

DeepSeek's R1 model and its distilled variants have demonstrated reasoning performance that rivals or approaches leading Western frontier systems, despite significantly lower reported training costs and compute budgets. While OpenAI's accusations center on unauthorized extraction from external APIs, a range of alternative explanations—rooted in DeepSeek's publicly documented methods—offer plausible accounts for these advances without invoking large-scale covert distillation. These approaches leverage internal synthetic data generation, reinforcement learning pipelines, open-source foundations, and architectural efficiencies that have become standard in the post-2024 era of efficient large language model development.

8.1 Internal Data Generation Methods

DeepSeek's technical reports emphasize self-contained pipelines for creating high-quality training data, bypassing reliance on external teacher models. Central to this strategy is the use of their own prior-generation models—particularly DeepSeek-V3 and intermediate reasoning-focused checkpoints—as autonomous generators and judges.

Key techniques include:

- Rejection sampling: The base model generates multiple candidate responses to a prompt, and a reward model or stronger judge (often another instance of the same family) scores them for correctness, coherence, and reasoning depth. Only high-scoring outputs are retained, creating a filtered, high-quality corpus.
- Self-play and iterative refinement: Models critique and improve their own outputs in multi-turn loops, simulating chain-of-thought enhancement without human annotation.
- Synthetic curriculum generation: The model first produces diverse problem sets (mathematics competitions, coding challenges, scientific reasoning tasks) at varying difficulty levels, then solves them with detailed step-by-step traces. This bootstrapping creates a self-reinforcing dataset rich in procedural knowledge.
- Reinforcement learning from AI feedback (RLAIF): Reward models derived from the same lineage provide preference signals, enabling policy optimization without external human-labeled data.

These methods scale efficiently on internal compute clusters. By generating billions of tokens of synthetic reasoning data directly from their own models, DeepSeek can achieve the density of high-quality examples needed for reasoning emergence—often more targeted than raw web-scraped or API-extracted corpora. Public benchmarks show that carefully curated synthetic data frequently outperforms noisier, broader datasets when focused on reasoning tasks, providing a credible path to R1's reported strengths in mathematics, code, and logical inference.

8.2 Open-Source and Self-Distillation Techniques

DeepSeek has openly built upon and contributed to the ecosystem of open-weight models, which accelerates progress without proprietary extraction. Many of their distilled variants explicitly use base architectures such as Qwen, Llama-3, or earlier DeepSeek releases, fine-tuned with reasoning-specific data.

Self-distillation plays a prominent role:

- A larger model (teacher) generates detailed reasoning traces or soft probabilities, which are then used to train smaller siblings or future iterations within the same family.
- Techniques such as chain-of-thought distillation transfer explicit step-by-step reasoning patterns, enabling compact models to mimic emergent behaviors.
- Progressive distillation: Successive generations refine capabilities incrementally, with each checkpoint serving as teacher for the next.

Because these processes occur internally, they inherit full access to logits, intermediate activations, and unfiltered outputs—far richer supervision than API-derived text. DeepSeek has released multiple distilled models (for example, R1-Distill series) alongside their flagship releases, demonstrating that self-distillation yields strong performance compression. Community reproductions using similar open-source pipelines have achieved comparable results on reasoning benchmarks, suggesting that DeepSeek's gains align with what is achievable through legitimate, self-contained methods rather than covert external harvesting.

8.3 Efficiency Gains Without External Extraction

Several architectural and training innovations allow DeepSeek to reach high performance with substantially less compute than earlier frontier models, reducing the incentive for risky extraction strategies.

Notable factors include:

- Mixture-of-Experts (MoE) architectures, which activate only subsets of parameters per token, dramatically lowering inference and training FLOPs while maintaining scale.
- Advanced optimizers and learning rate schedules that improve sample efficiency.
- Longer context windows and grouped-query attention mechanisms that enhance reasoning over extended sequences without proportional compute increases.
- Targeted pre-training and post-training curricula focused on reasoning-heavy domains (mathematics, programming, science), concentrating capability where it matters most rather than pursuing uniform breadth.

- Massive internal compute resources—reportedly tens of thousands of high-end GPUs acquired through domestic supply chains and hedge-fund backing—enable full-scale training runs that rival Western efforts in raw throughput.

These efficiencies compound: a model trained with less waste on more relevant data can outperform one trained with greater brute force but less focus. DeepSeek's public claims of training R1 at a fraction of the cost of equivalent Western models are consistent with these optimizations, not necessarily with stolen knowledge. Independent analyses of open-weight MoE models and reasoning-focused fine-tunes show similar capability leaps without API involvement, reinforcing that internal innovation provides a sufficient explanation for the observed advances.

Collectively, these alternative pathways—synthetic data bootstrapping, self-distillation on open foundations, and architectural efficiency—offer a coherent, publicly substantiated account of DeepSeek's progress. They align with global trends in AI research where diminishing returns on brute-force scaling have shifted emphasis toward smarter data generation and targeted optimization. While they do not disprove the possibility of external extraction, they substantially weaken the necessity of such claims to explain R1's capabilities.

9. Ethical and Legal Considerations in AI Distillation

The practice of knowledge distillation sits at the intersection of technical innovation and thorny questions of ownership, consent, and fairness in the AI ecosystem. When distillation occurs within a single organization using internal models and data, few ethical or legal issues arise. Controversy emerges primarily in scenarios involving unauthorized extraction from third-party APIs or models, as alleged in the OpenAI-DeepSeek case. This section examines the principal legal and ethical dimensions: violations of platform terms of service, the unsettled status of intellectual property rights over model-generated outputs, and growing calls for greater transparency and regulatory oversight to address these ambiguities.

9.1 Terms of Service Violations

Virtually all major frontier model providers—OpenAI, Anthropic, Google, Meta (for Llama APIs), and others—include explicit prohibitions in their terms of service against using API outputs to develop or improve competing machine learning models. Typical language forbids reverse engineering, scraping, or training derivative systems on generated content without express permission. These clauses aim to protect the substantial investments in frontier training while allowing legitimate research, personal use, and commercial applications that do not directly compete on model architecture or capability.

In the context of alleged unauthorized distillation, repeated, high-volume querying to harvest reasoning traces, soft probabilities (where accessible), or synthetic datasets would constitute a clear breach if proven. Providers argue that such activity constitutes misuse because it circumvents the economic model of pay-per-use access and undermines the incentive to build and maintain frontier systems. Enforcement mechanisms include account suspension, rate-limit throttling, output watermarking, behavioral detection, and, in extreme cases, legal action for breach of contract.

From the perspective of the accused party, the line can appear blurry: legitimate heavy usage (for example, extensive research prompting) generates similar outputs without intent to train competitors. The distinction often hinges on volume, pattern, intent, and scale—criteria that are difficult to prove definitively without internal logs. Courts have not yet fully adjudicated API-based distillation cases at frontier scale, leaving enforcement largely in the hands of providers through private contractual remedies rather than public litigation.

9.2 Intellectual Property in Model Outputs

The legal status of outputs generated by large language models remains one of the most contested areas in contemporary intellectual property law. Under current U.S. copyright doctrine, works created solely by machines without sufficient human authorship generally do not qualify for copyright protection. This principle extends to model-generated text, code, or reasoning traces: they are typically viewed as lacking the requisite originality and human creative input to be copyrightable in themselves.

However, this does not resolve the question of whether a provider can claim proprietary rights over outputs through contract. Terms of service often assert that users are granted a limited license to use generated content for personal or internal purposes, but explicitly prohibit commercial redistribution, training of competing models, or bulk aggregation for derivative works. Breach of these contractual restrictions can trigger civil claims for misappropriation, unjust enrichment, or violation of implied covenants, even absent copyright infringement.

Additional layers complicate the analysis:

- Trade secret law may protect the underlying model weights and training processes, but not the ephemeral outputs once they are lawfully generated and delivered.
- Database rights or sui generis protections (more common in the European Union) could apply to systematically collected output corpora if they represent substantial investment.
- In jurisdictions with stronger personality rights or moral rights doctrines, concerns arise over attribution or integrity of generated content used in training.

To date, no major court has definitively ruled on whether using API outputs to train a competing model constitutes actionable infringement or misappropriation. Pending litigation and regulatory scrutiny suggest this area will evolve rapidly, potentially leading to clearer boundaries or new licensing regimes that permit limited distillation under controlled conditions.

9.3 Calls for Transparency and Regulation

The DeepSeek controversy, alongside broader debates over training data provenance, model provenance, and synthetic data proliferation, has intensified demands for systemic reforms in AI governance. Stakeholders across academia, industry, civil society, and government increasingly advocate for mechanisms that promote accountability without stifling innovation.

Key proposals include:

- Mandatory disclosure of training data sources and methods for frontier models, including whether synthetic or externally sourced data was used and under what licenses.
- Standardized watermarking or fingerprinting of model outputs to enable downstream detection of unauthorized use in training corpora.
- Tiered API licensing models that explicitly permit research-oriented distillation under audit or with revenue-sharing provisions, while prohibiting competitive commercial use.
- International coordination on export controls, ethical guidelines, and mutual recognition of safety alignment standards to mitigate risks of safeguard erosion across borders.
- Independent auditing regimes or trusted intermediaries to verify compliance with terms of service and intellectual property obligations without disclosing proprietary details.

Proponents argue that transparency reduces mistrust, enables evidence-based policy, and prevents escalation of geopolitical tensions over unsubstantiated accusations. Critics caution that excessive disclosure requirements could disadvantage open research, favor incumbents with resources to comply, or expose vulnerabilities to adversarial attacks.

In the near term, voluntary commitments—such as those emerging from industry coalitions—and targeted regulatory frameworks (for example, in the EU AI Act or proposed U.S. executive actions) are likely to shape the landscape first. The OpenAI-DeepSeek episode illustrates the urgency: absent clearer rules and verifiable evidence, disputes over distillation risk devolving into proxy battles in the larger U.S.-China technology rivalry, with innovation and global cooperation as collateral damage. Establishing balanced, transparent norms will be essential to sustaining progress while safeguarding legitimate interests on all sides.

10. Future Directions and Recommendations

The OpenAI-DeepSeek controversy, whether ultimately substantiated or not, exposes structural vulnerabilities and misalignments in the current AI ecosystem: opaque training pipelines, asymmetric access to frontier capabilities, geopolitical tensions over technology transfer, and the tension between open innovation and proprietary protection. Addressing these issues requires proactive steps from providers, researchers, policymakers, and the broader community. This final substantive section proposes concrete directions forward, focusing on technical defenses, evidentiary standards, and pathways to more collaborative, open progress in artificial intelligence.

10.1 Enhancing API Defenses

Frontier model providers must evolve their defenses against unauthorized extraction beyond reactive rate limiting and behavioral heuristics. A multi-layered, forward-looking strategy could include:

- Advanced output watermarking and fingerprinting: Embed statistically detectable signals in generated text or token sequences that persist through fine-tuning and distillation, enabling post-hoc detection of whether a downstream model was trained on provider outputs.
- Logit perturbation and differential privacy techniques: Introduce controlled noise into API responses that degrades utility for bulk distillation while preserving single-query usefulness for legitimate users.
- Dynamic behavioral profiling: Employ machine learning models to monitor long-term account trajectories, detecting shifts from human-like iterative usage to programmatic, high-throughput patterns even when obfuscated.
- Tiered and auditable access models: Offer research-specific API tiers with higher quotas but mandatory logging, periodic audits, or usage attestations that explicitly permit limited distillation for non-commercial purposes under defined conditions.
- Cryptographic commitments: Explore zero-knowledge proofs or verifiable computation frameworks that allow researchers to demonstrate compliance (for example, proving that outputs were used only for evaluation, not training) without disclosing full datasets.

These measures must balance security with usability: overzealous restrictions risk stifling legitimate heavy research, collaboration, and education. Iterative deployment, coupled with transparent communication about changes, will be essential to maintain trust among power users.

10.2 Promoting Evidence-Based Accusations

Accusations of model theft or unauthorized distillation carry high stakes—commercial, reputational, and geopolitical. To prevent escalation into unsubstantiated claims or politicized narratives, the field should adopt stricter norms around evidence disclosure:

- Standardized forensic reporting: When providers detect suspected violations at scale, publish redacted but technically detailed summaries (for example, anonymized query pattern statistics, volume estimates, attribution signals) that allow independent experts to assess plausibility without compromising operational security.
- Third-party verification mechanisms: Establish trusted intermediaries—academic consortia, neutral auditing firms, or international standards bodies—that can review proprietary evidence under nondisclosure agreements and issue public attestations of findings.
- Preemptive transparency in accusations: When matters are escalated to government bodies or media, accompany claims with at least partial technical exhibits (comparative output samples, statistical fingerprints, or watermark recovery demonstrations) rather than relying solely on narrative summaries.
- Legal pathways over political amplification: Encourage resolution through civil litigation, arbitration, or contractual enforcement where evidence can be tested adversarially, rather than routing disputes primarily through national security committees where political framing may overshadow technical merit.

Adopting these practices would raise the bar for credible claims, reduce the incentive for speculative or exaggerated assertions, and foster a culture in which serious violations are addressed rigorously while protecting against false or opportunistic allegations.

10.3 Advancing Open AI Research

The most sustainable path away from extraction controversies lies in expanding legitimate, open alternatives that reduce dependence on closed frontier APIs for reasoning and capability advancement. Key opportunities include:

- Federated and collaborative synthetic data consortia: Multiple organizations pool anonymized, high-quality reasoning traces and problem-solution pairs under clear licensing terms, enabling collective distillation without unilateral extraction.
- Open-weight frontier equivalents: Accelerate development of truly open models (weights, training recipes, and evaluation harnesses fully released) that serve as shared teachers for distillation, lowering the incentive for covert API harvesting.

- Standardized distillation benchmarks and toolkits: Create public leaderboards and reproducible pipelines for self-distillation, rejection sampling, and synthetic curriculum generation, allowing researchers worldwide to replicate and improve upon state-of-the-art reasoning efficiency without proprietary access.
- Incentive alignment through licensing innovation: Explore hybrid models where providers offer permissive research licenses for distillation in exchange for attribution, co-authorship on resulting publications, or revenue-sharing on commercial derivatives.
- Global governance frameworks for frontier alignment: Coordinate international standards on safety red-teaming, refusal patterns, and transparency reporting to minimize divergence in deployed models, reducing national security anxieties tied to safeguard erosion.

By prioritizing openness where possible and rigorous protection where necessary, the AI community can shift from a zero-sum paradigm of guarded capabilities toward one of shared progress. DeepSeek's documented internal methods—synthetic bootstrapping, self-distillation, and efficiency-focused architectures—illustrate that rapid advancement remains achievable without breaching closed systems. Reinforcing these legitimate pathways, while fortifying defenses and evidentiary norms, offers the best prospect for ethical, innovative, and geopolitically stable development of artificial intelligence in the coming decade.

11. Conclusion

The controversy surrounding OpenAI's February 2026 accusations against DeepSeek encapsulates many of the defining tensions in the contemporary artificial intelligence landscape: the clash between proprietary innovation and open discovery, the fragility of API-based access in an era of rapid capability scaling, the difficulty of proving intent and method in complex technical disputes, and the entanglement of commercial competition with national security imperatives. At its core, the debate revolves around a single, seemingly straightforward technique—knowledge distillation—and whether it can plausibly serve as a vector for large-scale, undetected extraction of frontier-level reasoning capabilities through public interfaces.

This paper has approached the issue with deliberate skepticism grounded in technical realism and practical experience. Knowledge distillation is neither mysterious nor inherently illicit; it exploits redundancy in overparameterized models, leverages richer supervision through soft targets and temperature scaling, and operates comfortably within information-theoretic bounds. When performed internally with full-weight access, it routinely produces compact, high-performing derivatives. When attempted via external APIs, however, the process encounters severe practical constraints: finite rate limits, behavioral detection, financial

footprints, and the engineering overhead required for sustained evasion. The notion that millions of sophisticated, obfuscated queries could be executed covertly over months—yielding datasets sufficient to bootstrap R1's reported reasoning prowess—strains credibility when juxtaposed against the observable behavior of legitimate heavy users who rarely trigger aggressive interventions despite comparable or greater cumulative volume.

Alternative explanations for DeepSeek's advances prove far more parsimonious. Self-generated synthetic data, rejection sampling, reinforcement learning from AI feedback, self-distillation within open-weight lineages, and architectural efficiencies such as mixture-of-experts scaling offer coherent, publicly documented pathways to strong reasoning performance without recourse to unauthorized external harvesting. These methods align with global trends toward smarter, more targeted data curation rather than brute-force reliance on scraped or extracted corpora.

The absence of granular, publicly verifiable evidence—query logs, attribution fingerprints, comparative output analyses, or watermark recoveries—further weakens the accusations. While providers and governments may possess proprietary indicators justifying internal concern, escalation to congressional committees without accompanying technical disclosure invites skepticism about whether the claims reflect genuine malfeasance or serve broader strategic purposes in the U.S.-China AI rivalry. Framing distillation as a national security threat amplifies legitimate worries about safeguard erosion and asymmetric capability transfer, yet it also risks politicizing a technical domain where evidence should precede narrative.

Moving forward, the field would benefit from a dual strategy: fortifying API protections with watermarking, dynamic profiling, and auditable research tiers on one hand, while aggressively expanding legitimate open alternatives on the other. Collaborative synthetic data consortia, fully open frontier-weight models, standardized distillation benchmarks, and innovative licensing frameworks can reduce the incentive for covert extraction and shift progress toward shared, verifiable advancement. Evidence-based norms—mandatory partial disclosure in serious allegations, third-party verification, and preference for legal over political channels—would help separate substantiated violations from competitive posturing.

Ultimately, the OpenAI-DeepSeek episode serves as a cautionary reminder that hype, suspicion, and geopolitical anxiety can outpace technical reality. Artificial intelligence will continue to advance most effectively when guided by transparency, rigorous evidence, and a commitment to ethical norms rather than unsubstantiated narratives of theft. By prioritizing the former, the community can preserve the conditions for innovation while mitigating the very risks that fuel today's controversies. The path ahead lies not in closing borders around knowledge, but in building bridges strong enough to support collaborative progress in a domain that increasingly defines global power and possibility.

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The author has published ~ 5,000 AI-assisted papers at: https://www.researchgate.net/profile/Douglas-Youvan/research . Google Scholar has indexed these preprints, and if you want a particular reference, the AI mode of a Google search (Gemini) has efficiently catalogued these preprints.